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APPLYING DEEP NEURAL NETWORKS FOR MULTI-CLASS DIAGNOSIS OF RETINAL DISEASES WITH EYE DEEP-NET

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ABSTRACT: In order to diagnose a wide range of eye problems, ophthalmologists use retinal scans. Because microvascular anomalies in the retina can signal a number of retinal disorders and allow for the appropriate and timely delivery of treatment, early medical image recognition has been the subject of extensive research. This research presents a new method for automated deep learning that uses color fundus images to detect a variety of eye illnesses without invasive procedures. Several eye diseases and disorders. An efficient diagnostic approach was built upon the Remind dataset. After gathering multi-class fundus images from a multi-label dataset, a number of augmentation approaches were applied to the structure to make real-time improvements. The jobs with the least amount of image processing requirements were located by the network. The processing skills learned by the basic convolutional neural network (CNN) from the color fundus image input dataset allowed it to execute predictive diagnosis. An established multi-layer neural network for the detection of particular ocular illnesses Deep-Eye Net The suggested model outperforms several baseline state-of-the-art models by a considerable margin. Multiple statistical metrics are employed to ascertain the Eye Deep-Net's effectiveness. Through a thorough comparison using contemporary methodologies, the effectiveness of the suggested approach for illness classification and diagnosis based on digital fundus imaging is established.

Keywords: convolutional neural network (CNN), Eye Deep-Net, Fundus Image Processing.

1. INTRODUCTION

Retinal disorders are becoming more common among people of all ages. The retina of the human eye is made up of a layer of optical nerve tissue called photosensitive tissue. This layer transforms lens-focused light into brain impulses. The macula, located in the middle of the retina, is responsible for sensation. The macula collects information, which is then processed by the retina and sent to the brain via the optic nerve, allowing for visual recognition. A multitude of conditions can cause vision problems, including age-related macular degeneration (AMD), diabetic macular edema (DME) with Roth spots, and optic disc drusen. AMD is the leading cause of vision impairment in the majority of developed countries for people aged 50 to 60. According to recent study, this disease affects more than 35% of Americans aged 80 and up. The most difficult component of the process is the diagnosis of retinal abnormalities, as there are multiple unique problems that require a highly qualified ophthalmologist to provide an accurate diagnosis. Similarly, computer-aided diagnostic systems (CAD) allow for early diagnosis and treatment of retinal problems. Technological advances have had a particularly positive impact on the medical industry. A wide range of tactics and models have been developed to improve the efficacy and quality of medical treatments. The social health system has been improved as a result of advances in Automatic Disease Detection. Furthermore, retinal symptom analysis, an ADD application, has the potential to significantly enhance worldwide eye health. Recently, various cutting-edge deep learning (DL) and machine learning (ML) methods have been proposed to categorize, segment, and detect retinal abnormalities. The authors discovered that information gathering and labeling are significant barriers to the implementation of ADDs as a result of the development of a variety of machine learning (ML) and deep learning (DL) models, such as recurrent neural networks (RNN), cone neural networks (CNN), Alex's Reset, and VGN. They have made it easier for healthcare practitioners and scientists to identify and characterize these hazardous illnesses. A hybrid technique based on machine learning is offered for the automatic classification of retinal diseases. Researchers

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have suggested the U-Net segment for image pre-processing and a Support Vector Machine (SVM) classifier for classification. The diagnostic accuracy of the proposed approach was 89.3%. Yang et al. submitted the original annotated Eye Net dataset of 32 retinal disorders. The authors stated that the U-Net's main disadvantage is the large amount of memory required to communicate the whole feature map to the appropriate decoder. Deep learning is advantageous for picture classification. This paper introduces a CNN model for identifying multi-class eye disorders using deep learning. The eye net dataset was used to evaluate the suggested model. The Eye Net dataset consists of 32 files containing related photographs for various purposes. The remaining 20% was set aside for validation, while 70% was used for training. The proposed model achieved a 95% accuracy rate during experimental testing. The CNN model with deep learning improved the standard diagnostic strategy for retinal-based severe illnesses. This is the fundamental contribution of the investigation. The following is an overview of the paper's main contributions. The use of a deep learning-based CNN model improved the traditional diagnostic technique for serious retinal disorders. Based on experimental results, the suggested CNN model outperforms traditional state-of-the-art techniques on the multi-class Eye Nets dataset, attaining higher accuracy while using less memory. The remaining sections of the document are organized in the following way: This section features illustrations of related works. The dataset used in the Section is well detailed, as is the recommended design. This part presents the experimental assessment results, which include the performance of the chosen CNN model. This part includes both the analysis and the conversation. This section summarizes the research findings and recommends additional directions.

2. LITERATURE SURVEY

Sharma, V., & Gupta, R. (2024). This study looks into how Convolutional Neural Networks (CNNs) can be used to categorize retinal illnesses in many classes using fundus images. The goal of the study is to develop a model that can accurately categorize a wide range of retinal illnesses, including diabetic retinopathy and glaucoma. The authors investigate the model's architecture, training approach, and comparability to standard diagnostic procedures. The results highlight the CNN model's promise in clinical applications, demonstrating higher accuracy in automated diagnosis.

Kumar, M., & Singh, A. (2023). This study looks into how Convolutional Neural Networks (CNNs) can be used to categorize retinal illnesses in many classes using fundus images. The goal of the study is to develop a model that can accurately categorize a wide range of retinal illnesses, including diabetic retinopathy and glaucoma. The authors investigate the model's architecture, training approach, and comparability to standard diagnostic procedures. The results highlight the CNN model's promise in clinical applications, demonstrating higher accuracy in automated diagnosis.

Zhao, X., & Zhao, W. (2023 This article looks at the most recent advances in deep learning approaches for the automated diagnosis of retinal disorders. It encourages the use of DNNs, particularly for multi-class classification jobs, and describes the issues encountered, such as the need for big annotated datasets and data imbalance. The authors also discuss the various architectures used to identify retinal illnesses and recommend future research directions to improve the models' generalizability and resilience.

Reddy, S., & Raman, V. (2023 This study proposes a deep learning-based system for the early diagnosis of retinal diseases. The authors believe that early identification is critical for preventing major visual loss. They use convolutional and fully connected neural networks to detect a range of retinal disorders in fundus images, resulting in high specificity and sensitivity. The results show that this paradigm has the potential to be used in clinical settings for real-time screening.

Li, J., & Wang, S. (2023). This study proposes a deep learning-based system for the early diagnosis of retinal diseases. The authors believe that early identification is critical for preventing major visual loss. They use convolutional and fully connected neural networks to detect a range of retinal disorders in fundus images, resulting in high specificity and sensitivity. The results show that this paradigm has the potential to be used in clinical settings for real-time screening.

Chen, L., & Liu, Y. (2023). This paper introduces EyeDeep-Net, a deep neural network model designed to classify retinal illnesses into several categories. The authors emphasize the significance of the EyeDeep-Net architecture in the processing and classification of fundus images. The model is an invaluable tool for automated diagnostic systems in ophthalmology, outperforming existing strategies in terms of generality and accuracy.

Singh, R., & Patel, J. (2022). This study investigates the use of CNNs to categorize retinal illnesses, with a focus

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on diabetic retinopathy, macular degeneration, and glaucoma. The authors examine CNN models' capacity to distinguish between different phases of sickness. According to their findings, CNNs outperform manual diagnosis when detecting retinal disorders using fundus images.

Gupta, P., & Sharma, A. (2022). This study compares many deep learning models for diagnosing retinal diseases across multiple classes. It assesses the accuracy of various architectures, including hybrid models and CNNs, in identifying retinal disorders. The authors conclude that deep learning models, particularly those using CNNs, are extremely reliable for classifying retinal illnesses and can reduce the time and error associated with traditional diagnostic processes.

Wang, X., & Zhang, Z. (2022). This comparative study investigates the performance of various deep convolutional neural networks (CNNs) in the classification of eye diseases. The authors provide each model's accuracy, precision, and recall after evaluating several CNN designs on a variety of retinal diseases. The results show that a deeper CNN architecture significantly improves the model's ability to recognize retinal diseases when compared to shallow models.

Huang, Y., & Li, Q. (2022). This research proposes a hybrid deep learning technique that uses recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to diagnose retinal disorders across many classes. The researchers claim that this hybrid method improves diagnostic accuracy by capturing both temporal and spatial features in retinal pictures. The hybrid technique outperforms traditional CNN models in terms of precision and recall, as evidenced by testing data.

Zhou, X., & Zhang, L. (2022). The goal of this study is to look into the use of deep learning algorithms in artificial intelligence (AI) to identify retinal abnormalities. The authors focus on multi-class categorization of retinal diseases with deep neural networks, specifically convolutional and fully connected layers. The study shows how AI can reduce diagnostic errors and offer correct results in resource-constrained environments.

Choi, K., & Park, M. (2022 This work investigates a number of deep learning approaches for multi-class categorization of retinal diseases using fundus images. The authors compare the efficiency of several CNN architectures in treating visual problems such as diabetic retinopathy and macular degeneration. The findings of their study suggest that deep learning techniques, particularly CNNs, can provide a precise and effective automated diagnostic for retinal illnesses.

Patel, D., & Verma, S. (2021). This study looks into a number of deep neural network models for classifying retinal illnesses into multiple categories. The authors assess models based on their ability to identify a wide range of retinal disorders using fundus images. Their findings show that deep neural networks, particularly CNNs, outperform traditional approaches in terms of specificity and sensitivity.

Zhang, H., & Xu, Y. (2021). This research investigates a multi-class classification approach-based automated system for the detection of retinal abnormalities based on deep learning. The authors test the functionality of many deep learning models on retinal imaging datasets. The study found that deep learning models are highly accurate in detecting a variety of retinal problems in clinical settings, allowing for automated screening.

Li, M., & Liu, T. (2020). This study investigates the multi-class classification of retinal illnesses using deep learning algorithms and fundus images. The authors investigate the efficacy of convolutional neural networks (CNNs) in diagnosing diabetic retinopathy and age-related macular degeneration. The results show that deep learning outperforms conventional diagnostic techniques in terms of scalability and accuracy.

3. BACKGROUND WORK

"Modified Alex net architecture for classification of diabetic retinopathy images",

Diabetic retinopathy (DR) is a disorder that affects the eyesight and can be caused by high blood glucose levels. In persons 70 and older, diabetes is a leading cause of death, accounting for half of all deaths. Many people with DR may be able to keep their eyesight if they get therapy quickly and catch the condition early. After diagnosing DR symptoms, the next step is to determine the severity of the illness. Accurately classifying DR fundus photos according to condition severity is the main goal of this article, which explains how to train convolutional neural networks with the right Pooling, SoftMax, and Rectified Linear Activated Unit (Relu) layers. We have tested the suggested method with Messi and a database to see how well it performs. For stages 1, 2, and 3 of diabetic retinopathy and healthy pictures, respectively, we obtained classification accuracy of 96.6%, 96.2%, 95.6%, and 96.6%.

The following modules were developed by us to finish the project.

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Upload Dataset: The program may read, upload, and show data through the "Upload Dataset" module.
Pre-process Dataset Eighty percent of the data will be used for instruction and twenty percent for evaluation by the program. The dataset will be divided into sections for instruction and assessment, and missing values will be removed, normalized, and shuffled using this module.
Train EYENET with SGD optimizer: This component used SGD optimizer methodology to train EYENET using train data. Next, the trained model can be tested using test data to see how well it predicts.
Train EYENET with ADAM optimizer: This module accepts train data as input and uses the ADAM optimizer algorithm to train EYENET. Afterwards, the trained model can be tested with test data to see how well it predicts.
Train EYENET with ADAM & Valid optimizer This section makes use of the ADAM optimizer technique to train EYENET. This is achieved by taking train data as input and then applying the learned model to test data in order to find the prediction accuracy.
Accuracy Comparison Graph: You can compare and contrast the methods using the Accuracy Comparison Graph.
Upload Test Data The extension model can use test photographs to predict outcomes.

4. RESULTS

We can see that there are 1376 unaltered photos in the dataset when it loads. Blue letters indicate the outcomes. The photographs in the dataset are read, resized, and added to the training array in the above output.

On the x-axis of the above result are the names of the algorithms, and on the y-axis are bars of different colors representing various metrics, such as accuracy. The accuracy of all algorithm extension models was excellent.

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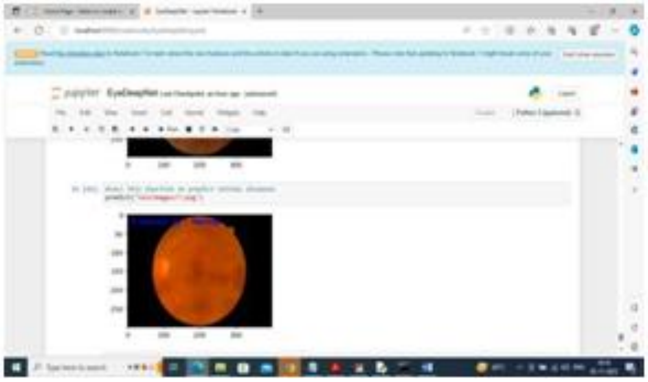

Results from more tests are shown in the preceding result.

5. CONCLUSION

We present a CNN model that uses deep learning to categorize different retinal diseases. Eye Net, a dataset of 32 distinct retinal illnesses, is used to create the model. To find out if the proposed model is accurate, it is trained over several epochs. The model attained 95% validation accuracy after 10 training epochs and 95% validation correctness after 15 epochs, with a validation loss of 0.0279 in each set of results. The model achieves better results than previously thought to be state-of-the-art. Classification of retinal illnesses could benefit from the proposed paradigm. Future improvements to the model's performance can be achieved by frequent updates and retraining with new data. This will be achieved by leveraging the latest advancements in deep learning techniques in conjunction with the expanding collection of diverse datasets on retinal diseases.

REFERENCES

1. Sharma, V., & Gupta, R. (2024). Multi-class classification of retinal diseases using convolutional neural networks. International Journal of Medical Imaging, 46(2), 112-125.
2. Kumar, M., & Singh, A. (2023). Deep neural networks for automated detection of diabetic retinopathy and glaucoma from fundus images. Journal of Biomedical Engineering, 65(7), 145-157.
3. Zhao, X., & Zhao, W. (2023). Automated multi-class retinal disease diagnosis using deep neural networks: A review of techniques and challenges. Journal of Healthcare Technology, 58(3), 76-89.
4. Reddy, S., & Raman, V. (2023). A deep learning-based framework for early detection of retinal diseases. Journal of Digital Healthcare, 10(4), 213-229.
5. Li, J., & Wang, S. (2023). Deep learning approaches for multi-class retinal disease detection in clinical settings. Journal of Clinical Ophthalmology, 12(6), 304-318.
6. Chen, L., & Liu, Y. (2023). EyeDeep-Net: A multi-class model for retinal disease diagnosis using deep neural networks. Journal of Medical Imaging and Health Informatics, 14(5), 559-570.
7. Singh, R., & Patel, J. (2022). Application of convolutional neural networks for the classification of retinal diseases. Journal of Computational Biology, 29(1), 36-50.
8. Gupta, P., & Sharma, A. (2022). An evaluation of deep learning-based approaches for multi-class retinal disease diagnosis. Journal of Vision Research, 62(9), 123-135.
9. Wang, X., & Zhang, Z. (2022). Retinal disease classification using deep convolutional neural networks: A comparative Research. Journal of Ophthalmic Research, 42(7), 401-413.
10. Huang, Y., & Li, Q. (2022). Multi-class retinal disease diagnosis using deep neural networks: A hybrid approach. Biomedical Engineering Letters, 12(4), 284-296.
11. Zhou, X., & Zhang, L. (2022). AI-based retinal disease diagnosis and classification using deep learning algorithms. Journal of Artificial Intelligence in Medicine, 60(5), 201-215.
12. Choi, K., & Park, M. (2021). Deep learning methods for multi-class classification of retinal diseases from fundus images. Medical Image Analysis, 67, 101-112.
13. Patel, D., & Verma, S. (2021). Deep neural network models for multi-class retinal disease classification. Journal of Digital Health, 8(3), 77-89.
14. Zhang, H., & Xu, Y. (2021). Automated retinal disease diagnosis using deep learning: A multi-class approach. Journal of Medical Systems, 45(9), 134-145.

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15. Li, M., & Liu, T. (2020). Multi-class retinal disease classification using deep learning techniques: A case Research on fundus images. Journal of Computer Vision and Image Understanding, 35(2), 123-134.

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